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AGENT-BASED MODELING AND SIMULATION FOR BUSINESS AND MANAGEMENT: A REVIEW AND TUTORIAL

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ABSTRACT

Agent-based modeling and simulation (ABMS) has become one of the most popular simulation methods. It has been applied to a wide range of application areas including business and management. This article introduces ABMS and explains how it can support management decision making. It covers key concepts and the modeling process. AgentPy is used to show the software implementation of the concepts. This article also provides a literature review on ABMS in business and management research using bibliometric analysis and content analysis. It shows that there has been an increase in the research that uses ABMS and identifies several research clusters across management disciplines such as strategic management, marketing management, operations and supply chain management, financial management, and risk management.

1 INTRODUCTION

This article introduces *agent-based modeling and simulation* (ABMS) and provides a review of its application in business and management research. We use the term *agent-based modeling* to refer to the process of developing an *agent-based model* (ABM and the plural is ABMs). The running of an ABM which is typically done in the context of an experiment is referred to as *agent-based simulation* (ABS). The term ABMS is used to refer to the whole process of developing and using an ABM in a simulation study.

ABMS has become one of the most popular simulation methods (Macal 2016). This is shown in the many applications of ABMS in various areas, such as marketing (Negahban and Yilmaz 2014), food supply chain (Utomo et al. 2018), epidemiology (Hunter et al. 2017), organizational studies (Gómez-Cruz et al. 2017), financial market (Todd et al. 2016), and transportation (Bazzan and Klügl 2013). The popularity of ABMS is also shown in the various simulation conferences in which ABMS have been an important feature, such as Winter Simulation Conference, Autonomous Agents and Multi-Agent Systems, Annual Modeling and Simulation Conference, as well as simulation journals such as Journal of Simulation, SIMULATION, Simulation Modeling Practice and Theory, and Transactions on Modeling and Computer Simulation. In fact, the majority of articles published in the Journal of Artificial Societies and Social Simulation use ABMS. There is also the London agent-based modeling meetup group where ABMS practitioners in London (UK) meet and share how they use ABMS to solve real-world problems. All of these show that ABMS has become more widely used. We will show in the literature review section that this is also true for business and management.

Given the increasing use of ABMS in business and management, the first objective of this article is to provide an introductory ABMS tutorial that covers key concepts, the modeling process and implementation using AgentPy. The purpose is to promote the use of ABMS in practice and research, especially in business and management. There have been several ABMS tutorials (e.g. Macal and North 2007, Macal and North 2010a, Onggo 2016). We believe this is the first tutorial written for business and management. The second

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objective is to review the business and management literature in which ABMS has been used. There is a lack of review on this topic. The most similar to our review is done by Gomez-Cruz et al. (2017) based on Scopus database. Our review uses Web of Science (WoS) database which complements their work. Furthermore, we apply quantitative methods (e.g. bibliometric analysis, historiography) to guide our content analysis.

The remainder of this article is organized as follows. First, the literature on the use of ABMS in business and management research will be reviewed in Section 2. Section 3 explains ABMS key concepts. The modeling process including a tutorial on how to implement an ABM using AgentPy will be presented in Section 4. Even though the example is in AgentPy, the concepts, modeling process and application described in this article are implementation-independent, so they can be applied to other software tools such as NetLogo (Wilensky 1999), Repast (North et al. 2013) and AnyLogic (www.anylogic.com). Finally, this article is concluded in Section 5.

2 ABMS APPLICATIONS IN BUSINESS AND MANAGEMENT

In this section, we review the applications of ABMS in business and management research. For this purpose, we search Web of Science (WoS) Core Collection, which is one of the main databases for business and management research, for relevant articles by running a query "agent AND based AND simulation AND (management OR business)" in the topic, published between 1970 and 2020, and filtered by WoS categories related to business and management (i.e. business, management and business finance). This query excludes relevant articles published in outlets outside the three categories, so the result is conservative but sufficient in providing an overview of the use of ABMS in business and management research. This search returns 263 articles and, after reading the abstracts, all of them are included in the following analysis.

To minimize the subjectivity and to make the analysis reproducible, bibliometric analysis has been conducted using the R package bibliometrix (Aria and Cuccurullo 2017). The bibliometric analysis is followed by content analysis in which we review the top locally cited articles in detail by reading the articles and identify how the ideas in these articles have developed over time.

Table 1 (left) shows the number of articles in the top ten categories. Some articles belong to more than one category but one of the categories is either management, business or business finance. Table 1 (right) shows the top ten publication outlets that accepts ABMS for business and management research. Figure 2 shows the number of articles over time. The earliest article was published at the Journal of Portfolio Management by Focardi (1996). The number of articles has shown an increasing trend since 2002.

Category	#Articles
Management	203
Business	113
Operations Res. / Management Sci.	50
Computer Sci. / Info. Systems	33
Economics	32
Engineering Industrial	25
Information Sci. / Library Science	24
Comp. Sci. Interdisciplinary Apps	22
Business Finance	20
Regional Urban Planning	13

Outlet	#Articles
Euro. J. of Operational Research	16
Eng. Construction and Architectural Management	7
Tech. Forecasting and Social Change	7
Industrial Marketing Management	5
Journal of Business Research	5
Electronic Commerce Research and Applications	4
IEEE Trans. on Eng. Management	4
Int. J. of Ops. & Prod. Management	4
Leadership Quarterly	4
Organization Science	4

Table 1: Top ten categories (left) and top ten publication outlets (right).

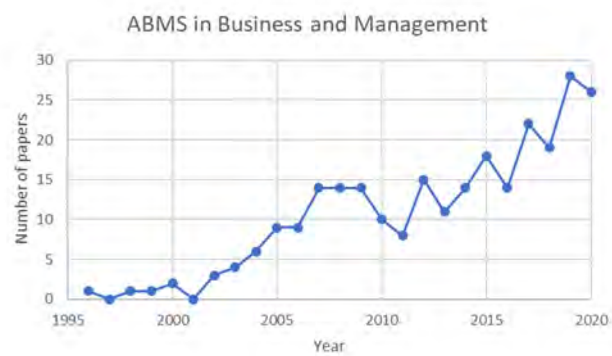

Figure 1: Number of articles on ABMS in Business and Management related categories (1995–2020).

To get the high-level view of the application of ABMS in business and management research, in Figure 2, we generate a co-word network of 50-most-used keywords from the selected articles. Each node in the network is a keyword used in the articles. We use keywords that are automatically generated by WoS from the titles of cited articles (i.e. Keywords Plus). When two keywords appear in the same article, an edge is created between the two keywords. The thickness of an edge between two keywords shows the frequency of the two keywords appear in the same articles. A thick edge suggests that the two keywords are strongly related. The colors show clusters identified by the software tool.

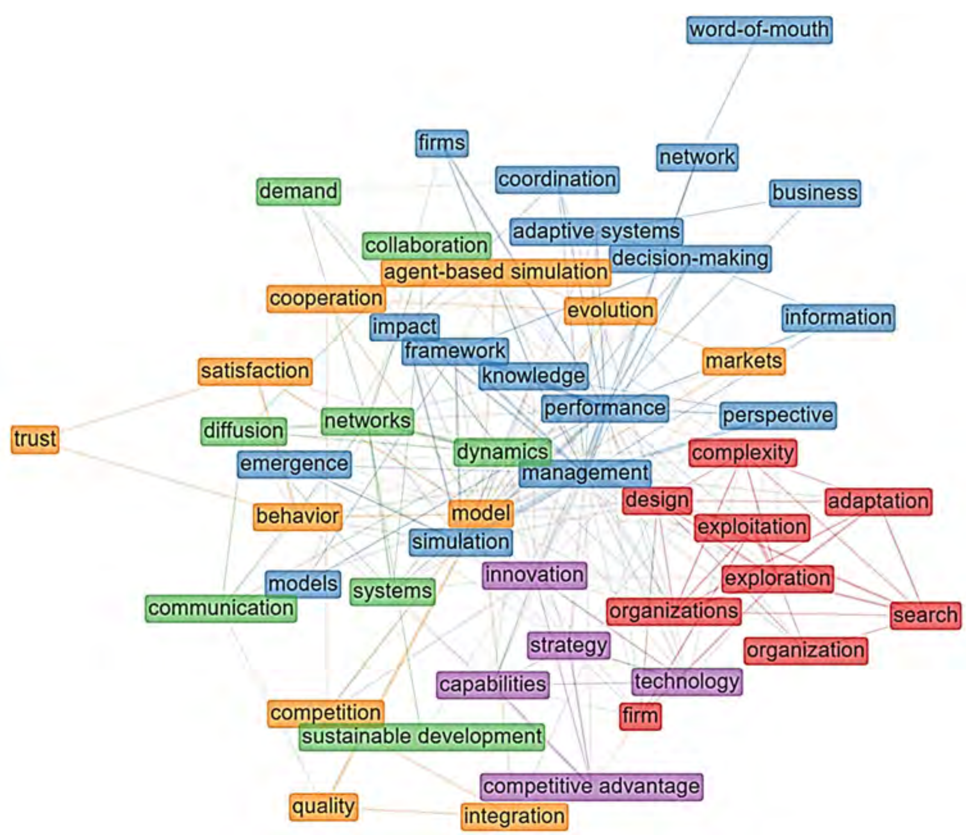

Figure 2: Co-word network of top 50 most-commonly-used keywords.

This network structure can help us understand the topics in which ABMS has been used. The keywords at the center of the network shows the topics that are shared by most articles, i.e. management, performance, dynamics and design. Given the search query, it is not surprising that the keyword “management” appears at the center of the network. The keywords “performance, design, network and dynamics” suggest that ABMS is used in research related to network dynamics or the performance estimation of a design. The keywords that are commonly associated with ABMS are also captured such as “emergence, behavior, and adaptive systems”. As we can see later, these are used to justify the use of ABMS. The keyword “exploration, exploitation, adaptation and organization” refers research in the area of organizational learning and strategic management. The keyword “networks, dynamics and diffusion” refers to the application of ABMS to model network dynamics and diffusion. The keywords “organizations, firms, markets, and innovation” are the key topics in management research where ABMS has been used. The keywords “communication, competition, cooperation, collaboration, and coordination” highlight the interactions between agents that are most commonly modeled and analyzed. The keywords “trust, quality, competitive advantage, satisfaction, and capabilities” are commonly used as parameters (or agent attributes) when comparing different scenarios or policies. The clusters show research focus areas, such as organizational learning and strategic management (red cluster), diffusion and network dynamics (green cluster), markets (orange cluster), innovation (purple cluster) and others/general management (blue cluster).

To know more about the detail when ABMS is used, we read the most locally cited articles in the set (i.e. the number of citations from any of the 263 articles). Local citations provide an indication of the impact of an article within this set of articles. Figure 3 shows articles that are locally cited more than once. The earlier articles tend to focus on making the case for the use of ABMS in their disciplines (e.g. Swaminathan et al. 1998; Anderson 1999; Garcia 2005; Nilsson and Darley 2006; Wilkinson and Young 2013; Busby et al. 2016). The latter articles tend to develop and use ABMS to answer their research questions and in doing so, they also justify why they choose ABMS. The most common argument is that ABMS is arguably one of the best tools to model or study a complex adaptive system which is characterized by the first four points in the list below. The following list summarizes the justification used by the articles in Figure 3 for using ABMS in their research.

- The complex interaction between agents is an important feature of the study (e.g. vertical or horizontal collaboration in supply chains, competition between firms in a market, word-of-mouth effect in product diffusion)
- The decision making is decentralized (e.g. local optimization by actors in supply chains, strategy committed by the competing firms in a market, purchasing decision by consumers).
- The heterogeneity of agents is important and affects the dynamics of the system.
- Agents show non-linear behavior (e.g. learning, path-dependence). Hence, the same stimuli to the same agent may trigger a different behavior depending on the time it happens and the agent’s past experience. The non-linearity may also be caused when the behavior of an agent is influenced by how the agent thinks the other agents will react to its action (e.g. Garcia 2005; Busby 2016).
- The closed-form analytical solution is difficult to obtain or does not exist due to the above characteristics.
- The behaviors at the agent (or micro) level and population (or macro) level interact. This is where the behavior of an agent is influenced by the behavior of the population (e.g. social norm) and over time, the behavior of the population is shaped by the agents. Hence, the behavior of an agent cannot be understood without analyzing the social environment in which the agents operate.
- The study is interested in analyzing both macro- and micro level behaviors.
- The authors want to analyze or predict emergence behaviors (Bonabeau 2002).
- The behavior of agents can easily be described using rules (e.g. if/then/else).
- The study is interested in modeling the mechanisms that generate behaviors (Epstein 1999).

The articles in Table 2 cover the following management disciplines: organization study, innovation and knowledge management, strategic management, marketing management, supply chain and operations management, accounting, and risk management. As the articles have been cited at least by two other articles in the set, it indicates that the application of ABMS in these disciplines may be more developed. The development of the research ideas is also confirmed by the historiography of these articles (Figure 3). The link between a pair of articles shows that the newer article cites the older article. Hence, the diagram shows how the ideas from Anderson (1999) and Swaminathan et al. (1998) influence the other articles. Hill and Watkins (2007) and Watkins and Hill (2009) form another group.

Article	#loc. citations
Anderson (1999)	9
Swaminathan et al. (1998)	8
Garcia (2005)	5
Delre et al. (2007)	5
Wilkinson and Young (2013)	4
Bonabeau (2002)	4
Hill and Watkins (2007)	4
Forkman et al. (2012)	3
Nilsson and Darley (2006)	3
Odehnalova and Olsevicová (2009)	3

Article	#loc. citations
Stummer et al. (2015)	3
Wall (2016)	2
Lin et al. (2005)	2
Tay and Lusch (2005)	2
Zhang and Zhang (2007)	2
Watkins and Hill (2009)	2
Amini et al. (2012)	2
Miller (2015)	2
Busby et al. (2016)	2
Gomez-Cruz et al. (2017)	2

Table 2: Articles that are locally cited for more than once.

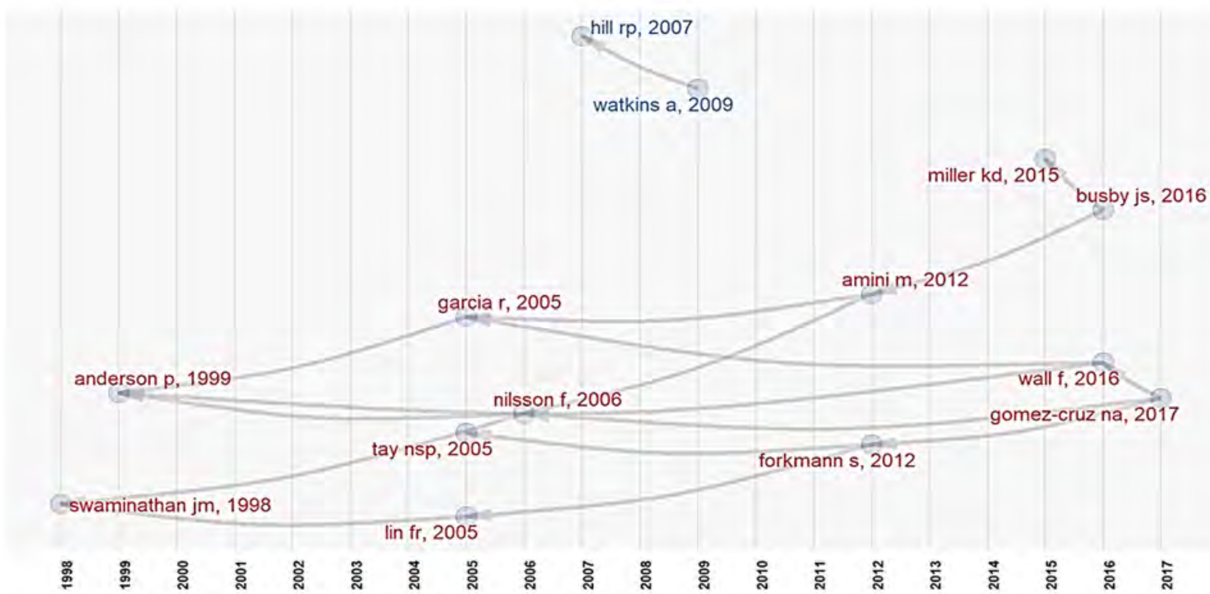

Figure 3: Historiography of the articles that are locally cited for more than once.

Complexity is a central construct in organization science that characterizes organizations and the environment in which they operate. Anderson (1999) argues that ABMS has the characteristics that are compatible with the characteristics of complex organizations. Hence, ABMS can be used to study organizations. Forkman et al. (2012) demonstrated this by developing an ABM to understand how networking strategy and power position of organizations affected the performance and survival of their relationship with other organizations. Likewise, Odehnalova and Olsevicová (2009) used an ABM to reproduce the evolution of a family business and a non-family business in terms of the number of employees, the amount of sales and the amount of assets by changing the parameters of the organizations such as investment in human resource and innovation. More examples can be found in Gomez-Cruz et al.

(2017). Despite these examples, Miller (2015) observed that these studies had made only modest contributions to advancing organization theory. Therefore, he proposed the use of critical realism as the philosophical perspective when applying ABMS in organization research.

In the supply chain and operations management discipline, Swaminathan et al. (1998) argue that ABMS is a natural choice for supply chain modeling given the decentralized nature of the decision making. They further presented an ABM of a supply chain. Nilsson and Darley (2006) justify the use of ABMS as a method to operationalize the complex adaptive system perspective in operations management. They also developed an ABM for a packaging company to test the impact of various policies (e.g. inventory, production plan) on the quality of customer service. ABMs can also be used for intangible mechanisms such as trust and power dynamics. For example, Lin et al. (2005) studied the effect of different trust mechanisms on supply chain performance in four market environments. In another example, Giannoccaro et al. (2018) developed a model to evaluate the impact of control strategy (i.e. how many suppliers should be controlled by a focal firm) on supply chain performance. One of the important parameters is the relative power of the focal company and its suppliers. Utomo et al. (2018) provide more examples from food supply chain.

Market can be viewed as a complex adaptive system because order emerges from the interactions of actors in the market in a self-organizing and bottom up way (Wilkinson and Young 2013). Hence, ABMS can be used to model and analyze the diffusion of innovation or new products (Garcia 2005; Wilkinson and Young 2013). Garcia (2005) demonstrated this by developing an ABM to evaluate innovation strategies (i.e. balancing research and development) on market share. Similarly, Delre et al. (2007) used ABMS to evaluate the effect of different promotional strategies for new product launch on market penetration. In another example, Stummer et al. (2015) developed an ABM to predict an innovation diffusion process in the context of competing products and repeated purchase decisions. Amini et al. (2012) used ABMS to understand the effect of production-sales policy on new product diffusion where the decision of consumers was affected by marketing activities and word-of-mouth. Kiesling et al. (2012) provides more example of innovation diffusion models in their review. In general, a diffusion model can be used to simulate the spread of a concept (e.g. innovation, perception, sentiment, knowledge) or an object (e.g. new product, document). Hence, diffusion models have been used to support management decisions related to managing risk perception, social media marketing, knowledge and information management, etc.

Apart from diffusion, in marketing, ABMS has also been used to analyze how the moral philosophies of salespersons and organizational ethical cultures affect revenues (Hill and Watkins 2007). Tay and Lusch (2005) developed an ABM to simulate competition in oligopolistic market where sellers accumulated wealth by making decisions on product and price offering. ABMS has also been used to analyze emergent market behavior. For example, Zhang and Zhang (2007) used ABMS to demonstrate how the decoy effect phenomenon in a competitive market emerged from the interactions of heterogenous consumers. Likewise, Watkins and Hill (2009) developed an ABM of a market that emerged from the interactions between three types of sellers (fair/altruist, opportunist and egoist) and buyers who applied different relationship marketing approaches. More examples can be found in Negahban and Yilmaz (2014).

Wall (2016) and Busby et al. (2016) have noted the lack of ABMS applications in management accounting and risk management research, respectively. Based on her review on the use of ABMS in managerial science, Wall (2016) developed an ABM to evaluate the effect of different incentive systems on firm performance in the presence of accounting errors. Busby et al. (2016) argued for the use of ABMS in managing social risk perception and developed an ABM that described the social amplification of risk phenomenon in which the nature and degree of the public response differed significantly from the objective assessments of risk. Because we only focus on the top locally cited articles, our review does not cover all disciplines such as finance (interested reader may consult Todd et al. (2016).

3 WHAT IS AGENT-BASED MODELING AND SIMULATION?

There are a number of terminologies that are similar to ABMS, such as multi-agent systems (MAS), agent-directed simulation, individual-based simulation and microsimulation. Some articles use different terminology, such as MAS and ABMS, to refer to the same thing. On the other hand, different articles may use the same terminology, such as ABMS, to refer to two different things. This is understandable given the fact that these related techniques have been applied in various application areas relatively independently. Macal (2016) provides a good overview of the different perspectives on ABMS.

This article defines ABM as "a simulation model that is formed by a set of autonomous agents that interact with their environment and other agents through a set of behaviors to achieve their objectives". In ABMS, modelers see the world as a set of interacting agents inhabiting in an environment. Hence, the main components of an ABM are agents, their behaviors and the environment where they live.

3.1 Agents and their behaviors

There is no consensus in the ABMS literature on the definition of an agent (Macal and North 2007). Instead, we find a spectrum of complexity in the definition of an agent. At one extreme, the composition of an ABM can be as simple as a set of homogeneous agents with simple behaviors, such as agents in Schelling *segregation model* (Schelling 1971) where all agents will move to a new place until they are happy and they have the same threshold for happiness. This type of agent is referred to as a pseudo-agent by Macal and North (2007). At the other extreme, an ABM can be formed by a set of heterogeneous agents with complex behaviors such as perception, planning and learning. For example, agents in the *social amplification of risk model* (Busby et al. 2016) observe how other agents react to a risk event and use the observation in combination with other factors (e.g. cognitive bias) to adjust their risk perception. Some agents play the role of the authority, media and public.

Consistent with the ABMS definition, this article defines an agent as "an entity that can make an independent decision in order to achieve its objectives". An agent can be human or non-human as long it can make a decision. Some decisions (or behaviors) are observable such as physical movements, purchasing a product, posting a product review, sharing information and consuming shared resources from the environment. Other decisions change the internal attributes of an agent such as the level of trust in another agent and the level of satisfaction on a service. These behaviors are not directly observable by other agents.

From the ABMS definition, agents are autonomous. Hence, an ABM does not have a central controller that coordinates the behavior of agents. Each agent can make an independent decision. The interactions between agents may generate a certain pattern that appears at the population level (known as *emergence behavior*) such as the formation of ghettos in the segregation model and the public amplification of risk in the social amplification of risk model. Both emergence behaviors are not coded in the model, but they emerge from the independent decisions made by the agents (e.g. moving to a new place in the segregation model, adjusting personal risk perception in the social amplification of risk model). Arguably, the main advantage of ABMS comes from its ability to generate (and explain) emergence behavior from local interactions between agents. The above behavioral rules are followed because each agent wants to achieve its objectives (e.g. an agent wants to be happy in the segregation model, or wants to reduce their exposure to risk in the social amplification of risk model).

When we develop an ABM, it is important to understand the difference between agent and agent type. An agent type is a modeling construct that represents all agents that can be identified by using the same set of attributes and are able to perform the same set of behaviors. In a hospital model, the types of agent may include patient, clerk and doctor. A patient is an agent type because all patients can be identified by using the same set of attributes (e.g. patient ID/social-security number and severity level) and are able to perform the same behaviors (e.g. arrive at the clinic, complete a form). From an agent type, one or more agents of the same type can be generated during a simulation. For example, during a simulation run, two patients called Joe and Jane are generated from the agent type patient. Both Joe and Jane have a unique ID. They can also perform the same behaviors, such as arrive at the hospital, but their arrival time and method of transport can be different. Hence, an agent type is defined during model development by specifying its attributes and behaviors, whilst agents are created from an agent type when we run the model (i.e. during a simulation) and their attributes need to be initialized. Heterogenous agents are created by assigning a different value to the same attribute of each agent.

3.2 Environment

The second component in an ABM is the environment where the agents live. The environment can be spatial or relational. The spatial environment refers to the location where an agent lives, such as a city or coordinates. The relational environment refers to the connections between agents, e.g. social network, transportation network or supply chain network.

The environment is an important part of an ABM because it may affect agents and their behaviors. In the segregation model, an agent makes a decision to move or to stay based on the state of its neighborhood. Likewise, in the social amplification of risk model, an agent updates its risk perception based on the observable behavior of other agents. Furthermore, the environment can be used as a medium for the interactions between agents (i.e. indirect interactions between agents). In this case, an agent may change the environment, which consequently affects other agents. In the segregation model, when an agent moves, the agent changes the state of the old and new neighborhoods. These changes will affect the decisions made by other agents in the old and new neighborhoods. All of these show that the environment is an important part of an ABM.

Often, we need to model an environment to be dynamic, i.e. the environment changes even when all agents do nothing to it. In other words, an environment can have behaviors. Hence, in the implementation, if the software tool does not support dynamic environment, it can be implemented as an agent.

Commonly used types of environment in ABMS include grid, continuous space (or Euclidean space), Geographical Information System (GIS) and network. A grid creates cells that are structured in one or more dimensions. For example, a 2D grid creates a chessboard-like environment where each agent lives in a cell. This is a structure used in many popular ABMs including the segregation model. In an *n*-dimensional continuous space, the location of an agent is represented by a vector $(x_1, x_2, .., x_n)$. It creates a more realistic spatial environment than grid. A GIS enables us to create the most realistic-looking spatial environment in which agents live in a geographical area. GIS typically uses a longitude-latitude coordinate reference system. A network is used to create a relationship network between agents. The relationship can be physical (such as a road network or a water-distribution network) or non-physical (such as a social network or a supply chain network). A network can be created empirically using real-world network data or theoretically using an algorithm, such as small-world, scale free or random. Some tools allow us to implement our own network-generator algorithm (e.g. Repast).

We can add several layers of environment type in an ABM. For example, in a communications-network simulation, we can define three layers of environment, such as a grid, to model all the cell stations that serve the agents' mobile phones, a continuous space to model the physical location of agents and a network to represent the current active mobile communications between agents.

4 ABMS MODELING PROCESS

The ABMS modeling process is not different from other simulation methods. The first step in simulation modeling is to translate a messy real-world problem into a (structured) analytics problem. This is where problem structuring methods can play an important role. From this problem formulation, we create a conceptual model. After validating the conceptual model with stakeholders, we can implement the conceptual model into a computer simulation model. The simulation model needs to be verified and validated before running any experiment using the model. Finally, we draw conclusion from the insights gained from the experiments and make a decision. In addition, we also need to collect data to support the various stages of the modeling process (e.g. system documentation for the conceptual modeling, historical data for the simulation model development and performance data for validation). This does not mean that the process is linear. It may require several cycles before a valid conclusion can be made from the simulation study. ABMS textbooks (e.g. Grimm & Railsback 2005) provide more detailed explanation on ABMS modeling process.

4.1 Conceptual Modeling

In simulation modeling, we select a certain portion of the real world system to be simulated for specific objectives. The process of capturing the essential elements of the system is referred to as conceptual modeling and the resulting model is referred to as a simulation conceptual model. There is no consensus in the literature on the definition of a conceptual model in simulation (Robinson 2008). He discusses and compares a number of different definitions. One of the definitions is that a conceptual model is "a non-software specific description of the computer simulation model (that will be, is or has been developed), describing the objectives, inputs, outputs, content, assumptions and simplifications of the model" (Robinson 2008). Using this definition, a conceptual model defines objectives, inputs, outputs, and model content.

Objective is arguably the most important component because if we do not get it right, we will waste our simulation modeling effort by solving a wrong problem. In ABMS, the objectives can be divided into two categories:

- **Using known micro to research the unknown macro**: in this category, the objective is to explore what would happen at the population level if we know the behaviors of the interacting agents. Hence, we are exploring the implications of known agent-level mechanisms/behavior on (unknown) population-level behavior. For example, the segregation model can be used to explore the behavior that may emerge at the population level if every agent does not want to live as a minority in its neighborhood. Hence, in the ABM, we implement the agents with the behavior that we want to test, let them interact with other agents, and observe the behavior that emerges at the population level. This objective category applies a deductive reasoning.
- **Research the unknown micro to explain known macro**: in this category, we want to test our hypothesis that a known behavior at the population level can be explained by certain behaviors of the agents. In other words, we want to know the mechanisms/behaviors at the agent level that explain a known population-level behavior/phenomenon. This category is more challenging because we apply an abductive reasoning. Hence, even after we implement the behavior of the agents in the model and we can reproduce the known population-level behavior, we can only conclude that our hypothesis (i.e. the behavior of the agents) is one of the possible explanations of the known behavior at the population level.

The *outputs* are closely linked to the objective, i.e. they are used to estimate key performance indicators (KPIs) that allow us to achieve our objective. The *inputs* are the experimental factors that we can vary so that we can understand their effect on the outputs. The inputs can be decision variables that represent designs or policies that are under decision maker's control, or uncontrollable variables that represent external factors that are typically beyond the decision maker's control.

The *model content* is the non-software specific representation of the simulation model that will be implemented. Hence, implicitly, the representation includes the model boundary, level of detail, assumptions and simplifications. The non-software specific adjective is important for two reasons. First, the conceptual model needs to be communicated to project stakeholders who may not be familiar with the simulation software. The second reason is that we do not need to change the representation when we change the simulation software in the future. This is useful for models that will be used regularly. While the conceptual-model representations in DES and SD have been dominated by process-flow and stock-and-flow diagrams, respectively, there has not been a common standard for conceptual-model representation in ABMS. Onggo (2013) reviewed five conceptual model-representation methods that had been used for ABMS (i.e. pseudocode/flowchart, Petri Nets, DEVS, UML and BPMN). Onggo and Karpat (2011) demonstrated how ABMs could be represented using BPMN. Siebers and Onggo (2014) explained how UML could be used to represent ABMs. UML's state chart diagram is also supported by ABMS tools such as AnyLogic and Repast.

4.2 Implementing ABM using AgentPy

AgentPy is an open-source library for ABM development in Python. It is optimized for interactive computing with Jupyter Notebooks and offers tools for various scientific applications, including parameter sampling, experiments over multiple runs, interactive simulations, stochastic processes, and sensitivity analysis (Foramitti, 2021). The software is available at https://github.com/JoelForamitti/agentpy. The code used in this tutorial article is available from https://mybinder.org/v2/gh/stephanong/abms_tutorial/HEAD.

To make the explanation more concrete, this article will use a social media marketing case as an example. This case is chosen because it is simple but good enough to highlight ABMS key concepts. The model represents a market with a finite number of consumers for a product (i.e. no competition). Initially, all consumers are non-adopters. A consumer can become an adopter when it receives an advertisement that is broadcasted to all agents in each time step, or when the consumer receives word-of-mouth (WOM) messages from its neighbors. Once a consumer becomes an adopter, it will stay as an adopter until the simulation ends. The objective of the model is to estimate the impact of WOM and advertisement on product sales. This example is taken from Grigoryev (2018). A video tutorial that shows how to implement the same model using AnyLogic can be found in https://youtu.be/ZwVo3MU0Azo.

To develop an ABM in AgentPy, we need to import the library (`agentpy`) and implement three classes: Model (to specify the ABM which comprises agents and environment), Agent (to specify an agent type which comprises attributes and behaviors) and Environment (to define the layers of environment in which the agents live). This model has one agent type, i.e. consumer. A consumer agent has the following attributes: `ad_effectiveness` (the probability that a non-adopter will become an adopter after receiving an advertisement), `adoption_fraction` (the probability that a non-adopter will become an adopter after receiving a WOM message), `contact_rate` (the number of WOM messages sent in each time step by an adopter), and `is_adopter` (False if the agent is non-adopter and True for adopter), and `become_adopter` (if True, the consumer will become an adopter in the next time step. Otherwise, the consumer will stay in its current state). When an agent is created during a simulation run, its `setup()` method is called, which is used to initialize the attributes of the agents. Another method `get_neighbors()` is defined for the agent to access their neighbors, i.e. all agents that are directly connected to it in the network. We use `networkx` library for the network environment.

We implement the consumer behaviors in the methods `step()` and `adopt()`. The first line inside method `step()` checks if the consumer is already an adopter. If it is a non-adopter, `adopt()` is called to check if the agent will become an adopter due to the influence of advertising. In contrast, if it is an adopter, it will send WOM messages to several agents as specified in its `contact_rate`. The recipients of WOM messages are selected randomly from its neighbors. It will then check if the recipient is an adopter. If not, the recipient's method `adopt()` is called to check if it will become an adopter due to the influence of WOM. Please note that at the end of methods `step()` or `adopt()`, the state of the agent will not change. The change will be done in method `update()` which is called after all agents have decided whether they want to become an adopter in the next time step.

```
class ConsumerAgent(ap.Agent):
    def setup(self):
        self.ad_effectiveness = 0.01
        self.adoption_fraction = 0.01
        self.contact_rate = 1
        self.become_adopter = False
        self.is_adopter = False

    def get_neighbors(self):
        self.neighbors = self.network.neighbors(self).to_list()

    def step(self):
```

```
        if self.is_adopter:
            for _ in range(self.contact_rate):
                partner = self.neighbors.random()
                if not partner.is_adopter:
                    partner.adopt(self.adoption_fraction)
        else:
            self.adopt(self.ad_effectiveness)

    def adopt(self, p):
        if self.model.random.random() < p:
            self.become_adopter = True

    def update(self):
        if self.become_adopter:
            self.is_adopter = True
            self.become_adopter = False
            self.model.n_adopters += 1
```

Next, we need to define the ABM by overriding four methods: setup, step, and update and end. When a simulation is started, it will call method `setup()`. This is where we add agents and environment into the model. AgentPy supports three types of environments. They are `Grid` (discrete space), `Space` (continuous space), and `Network` (connection/relation between agents). In the code below, we first create a small-world network. This is followed by adding several agents to the model. Finally, we add the small-world network to the model, link the agents to the network, and call `get_neighbors()` for each agent. The built-in variable `p` is used to access the simulation parameters that we will define later.

The method `step()` is used to define what agents will do in each time step. In this model, all agents will run their `step()` method. The method `update()` is called after the methods `setup()` and `step()` are completed. Hence, it is typically used to record population-level outputs and to synchronize the state changes in all agents to avoid any bias that may arise from the ordering of which agents are executed. In this model, all agents will run their `update()` method. Then, we calculate the number of adopters and record the value. If needed, we can override method `end()` which will be executed when the simulation ends. In this model, we ask all agents to record their final state.

```
class MarketModel(ap.Model):
    def setup(self):
        graph = nx.watts_strogatz_graph(
            self.p.n_agents,
            self.p.n_neighbors,
            self.p.network_randomness)

        self.n_adopters = 0
        self.agents = ap.AgentList(self, self.p.n_agents, ConsumerAgent)
        self.network = self.agents.network = ap.Network(self, graph=graph)
        self.network.add_agents(self.agents, self.network.nodes)
        self.agents.get_neighbors()

    def step(self):
        self.agents.step()

    def update(self):
        self.agents.update()
```

```
        self.record('n_adopters')

    def end(self):
        self.agents.record('is_adopter')
```

Next, we need to define the simulation parameters that are accessible by all model objects (i.e. agents, environments, and the model itself) via a built-in variable `p`. The parameter `steps` will be used automatically to define the maximum number of simulation runs, and `seed` will be used as a seed for the model's pseudo-random number generator, which allows for reproducible results. Then, we create the model and supply the parameters. We can run the model using method `run()` which is inherited from the class `Model` (hence, we do not need to define it). We store the simulation output in dictionary `results`. Finally, we retrieve the data and plot it using `matplotlib` library. Detailed information and more examples can be found from the AgentPy documentation.

```
parameters = {'seed': 42, 'steps': 300, 'n_agents': 1000,
    'n_neighbors': 2, 'network_randomness': 0.5
}
model = MarketModel(parameters)
results = model.run()
data = results.variables.MarketModel
ax = data.plot()
```

4.3 Verification and Validation

Stakeholders will need assurance that the ABM that is used as a decision-support tool is valid before they make a decision based on the model. We differentiate between verification and validation. Verification checks the correctness of a computer simulation model against its conceptual model. The objective is to ensure that a conceptual model has been implemented correctly in the computer simulation model. It is similar to finding and correcting bugs in computer programming. Visual interactive simulation tools such as AnyLogic provide debugging functionality for model verification. For library-based tools, we can use unit testing tools (e.g. Collier and Ozik 2013, Onggo and Karatas 2016).

The objective of model validation is to make sure that a simulation model is fit for its purpose by comparing the output of the simulation model with the expected output. The expected output can be obtained from empirical data or analytic/theoretical models. Since both DES and ABMS are typically used to represent stochastic dynamic systems and need to track the entities or agents during the simulation, the validation techniques commonly used in DES (Sargent 2013) are also suitable for ABMS. The validation techniques include face validation, operational validation, white-box validation and black-box validation. Sargent (2013) provides a good tutorial on validation methods that are also applicable to ABMS. However, model validation in ABMS is especially demanding. First, there is a need to validate ABMs at various levels (agent level, system level and, possibly, some intermediate levels). A second challenge arises due to the fact that we often need to represent behavior in ABM using rules or algorithms. Hence, we need to check if the rules used in our ABM validly represent the rules used by real-world agents. The heterogeneity of the agents makes this issue even more challenging. Finally, an ABM often requires high-fidelity data, which are not always available. Hence, validation using empirical data may not always be possible. Given these challenges, research that creates validation techniques and tools for ABMS (e.g. Collier and Ozik 2013; Onggo and Karatas 2016) is needed. These tools can help to increase the confidence of stakeholders when using ABMS for decision-making.

ABMS has increasingly been used to explain social phenomena or systems that exhibit emergent behavior which requires us to research the unknown agent-level mechanisms/behaviors to explain a known population-level behavior. As mentioned earlier, this approach uses an abductive logic. Hence, empirical validation is virtually impossible. In this situation, the credibility of the study depends on the explanatory power of the model (Onggo et al. 2019). Onggo et al. (2019) explain methods that can be used to improve the credibility of ABMS conducted in this context.

4.4 Documentation

Developing a simulation model can be expensive. Some models may be used regularly and need regular updates, especially with the digital twins or symbiotic simulation (Onggo et al. 2021). Some organizations may use their simulation models to gain a competitive advantage. For these reasons, some organizations may treat their models as assets. Hence, model documentation is important. In research, model documentation is equally important. This is because a good model documentation is needed to allow other researchers to reproduce the findings from a simulation study.

One of the most popular documentation protocols for ABMS is ODD which stands for "Overview, Design concepts, and Details" (Grimm et al. 2006). It was reported to have been used in more than 50 articles (Grimm et al. 2010). Having achieved the critical mass, they could evaluate the effectiveness of ODD and proposed several updates (Grimm et al. 2010, Grimm et al. 2020). The ODD protocol provides a checklist that covers key features that we expect from an ABM. This checklist helps to promote a more rigorous formulation of ABMs. Another documentation guide is STRESS (Monks et al. 2019). Similar to ODD, it provides a checklist that promotes reproducibility. The checklist covers the models, data, experimentation, implementation and code access. STRESS has been applied to describe an epidemic model (Taylor et al. 2018) and a food supply chain model (Onggo and Utomo 2021).

5 CONCLUSION

We have shown that ABMS has been in business and management research. Although ABMS is yet to become a mainstream method in management and business research, the number of articles that use ABMS has increased. Like other OR/MS tools, it is important to know how to use ABMS correctly. This article has provided an introductory tutorial in ABMS that explains the key concepts, the model development process, and the software implementation using AgentPy. In the future, we will extend the literature review to include more databases such as Scopus. We will also analyze the learning experience and cognitive process of business and management students when learning ABMS (e.g. Kogler and Rauch 2020).

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